SUBMISSION OF PROPOSAL FOR TOPIC APPROVAL IN THE FACULTY OF SCIENCE AND TECHNOLOGY

PROPOSAL FOR TOPIC APPROVAL TO BE SUBMITTED TO THE UNIVERSITY OF MUMBAI FOR THE PH.D DEGREE IN THE SUBJECT OF COMPUTER ENGINEERING.

Title of the topic	:	Multi-Modal Deep Learning Framework for Crop Phenology Detection and Harvest Scheduling Using Time-Series SAR–Optical Remote Sensing.
Name of the student	:	Algat Yogita Shravan
Basic Qualification	:	ME Computer
In the case of Ph.D. student Year of Passing of PET/NET/SET/M.Phil /GPAT/GATE (Teaching Experience)	:	PET 2024
Name of the Research Supervisor/Guide	:	Dr. Shreya Nandkumar Patankar
Date of Superannuation/Retirement of the Research Supervisor/Guide	:	23/08/2039
Name of the Research Centre	:	K J Somaiya Institute of Technology
Signature of the Student	:	
Signature of the Research Supervisor/Guide	:	17/12/25

Date:

K J Somaiya Institute of Technology * Sion Mumbai 400 022

Seal of College/

30/03/26

Department Signature of
Head/Director/Principal
Research Centre

Principal
K J Somaiya Institute of Technology
Sion (E), Mumbai - 400 022

A Topic Approval **Seminar** on

Multi-Modal Deep Learning Framework for Crop Phenology Detection and Harvest Scheduling Using Time-Series SAR–Optical Remote Sensing.

Submitted in partial fulfilment of the requirement for the degree of PhD

In

Science and Technology

(Computer Engineering)

By

Algat Yogita Shravan

Admission/ Registration No: 2220240788

Under the guidance of

Dr. Shreya Nandkumar Patankar

Department of Computer Engineering

K J Somaiya Institute of Technology

Somaiya Ayurvihar Complex Eastern Express Highway Near Everard Nagar, Sion East, Mumbai, Maharashtra 400022

मुंबई विद्यापीठ

University of Mumbai

2025-26

CERTIFICATE OF APPROVAL

This is to certify that **Algat Yogita Shravan** has delivered a topic approval seminar on **"Multi-Modal Deep Learning Framework for Crop Phenology Detection and Harvest Scheduling Using Time-Series SAR–Optical Remote Sensing."** on 17th December 2025 and submitted a report in **K J Somaiya Institute of Technology** Sion Mumbai, in the partial fulfilment of the degree of PhD in the Science and Technology (**Computer Engineering**).

17/12/25

Supervisor
(Name and Signature)
Dr. Shreya N. Patankar

Subject Expert Internal
(Name and Signature)
(Dr. Mansing Rathod)

Subject Expert External
(Name and Signature)
(Dr. Shrinivas Govilkar)

Head of the Department
(Name and Signature)

23/12/25

PhD Coordinator
(Name and Signature)

K J Somaiya Institute of Technology * Sion Mumbai 400 022

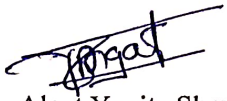
30/03/26

Principal

Principal
K J Somaiya Institute of Technology
Sion (E), Mumbai - 400 022

DECLARATION

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.



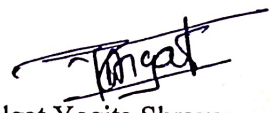
Algat Yogita Shravan
Registration No: 2220240788

Date: 17/12/2025
Place: Mumbai

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my seminar guide, **Dr. Shreya Nandkumar Patankar**, for her invaluable guidance, encouragement, and support throughout the preparation of this seminar. Her insights and expertise have greatly contributed to the depth and quality of my work.

I also extend my heartfelt thanks to **Dr. Hariram Chavan**, my PhD coordinator, for his continuous support, valuable suggestions, and encouragement in shaping my research direction. His guidance has been instrumental in refining my understanding of remote sensing and deep learning in agriculture.



Algat Yogita Shravan
Registration No: 2220240788

Abstract

Accurate crop wise phenology detection and timely prediction of harvest schedule are essential for effective agricultural management practices, government policy making and yield estimation. Traditional field-based monitoring, data capturing and single-sensor based remote sensing approaches are often limited with temporal coverage, high costs, and sensitivity to cloud conditions. The proposed study will focus on a multi-modal deep learning framework for crop phenology detection and harvest scheduling using time-series Synthetic Aperture Radar (SAR) such as Sentinel-1A and optical remote sensing data like Sentinel-2A/2B. This research will start with Ground Truth (GT) crop specific sample data collection. It will cover balanced samples of all types of crop in nashik region.

The proposed framework integrates multi-temporal Sentinel-1 SAR backscatter features with spectral and vegetation indices based information derived from Sentinel-2 optical imagery to detect crop structural and physiological characteristics during the growing season. The Data Preparation including radiometric and atmospheric correction, speckle filtering, cloud masking, etc., and phenology-base field labelling and mapping, is performed to build a robust multi-crop phenology spectral signature dataset. Deep learning models capable of learning temporal dependencies are employed to identify key crop growth stages such as Germination, Tillering, Grand Growth and Maturation.

Phenology map parameters are further utilized to estimate optimal harvest schedule and used explainable AI (XAI) to build trust on models. The proposed framework will provide a scalable and reliable solution for operational crop monitoring and decision support in precision agriculture.

Keywords: Precision Agriculture, Remote Sensing, Harvest Schedule, Deep Learning, Multi-modal.

CONTENTS

Abstract.....i
List of Figures.....iii
1. Introduction.....1
2. Aim of Research.....2
3. Objectives of Research.....3
4. Research Background (Literature Review) and Significance of Research.....3
5. National Status.....7
6. International Status.....8
7. Research Hypothesis.....9
8. Research Rationale.....9
9. Research Methodology.....10
10. Statistical Plan.....13
11. Limitations of Research..... 14
12. Expected Outcomes of Research.....14
13. Conclusion and Future Work.....15
14. Bibliography.....16

List of Figures & Tables

Fig 1. Proposed System crop phenology classification and harvest scheduling.....10

Table1. Crop Growth Duration.....13

1. Introduction

Agriculture remains a key point of economic development and food security, especially in agriculture-dependent economies and developing countries like the India where livelihoods are still depends on farming activities. However, factors like climate variability, limited natural resources, and the demand for higher productivity increased the need for smart and data-driven agricultural solutions. Hence, advanced technologies such as remote sensing and deep learning are playing a crucial role in transformation of traditional farming into precision agriculture systems[3], [7].

Accurate crop classification is the need of smart agriculture for agricultural monitoring, decision-making support system, crop management, yield estimation, and resource allocation. Traditional ground-truth monitoring methods are taking too much time , person specific, cost-oriented, less transparency and scalability issues. Satellite remote sensing, particularly through Sentinel-1 (SAR) and Sentinel-2 (optical) missions, offers consistent monitoring with 7-days repeat cycle for large-scale observations, enabling efficient crop mapping. Prior studies indicate that incorporating multi-temporal satellite datasets significantly enhances classification performance compared to single-date or single-source data [26], [31].

Nowadays, researchers focus on multi-modal data integration for improving agricultural analytics. The Multi-fusion of optical and SAR time-series improves early crop identification and reduces the possibility of errors occurred due to cloud inferences [1], [15]. Furthermore, integrating satellite imagery with climate features and environmental features enables a detailed understanding of crop growth behavior and phenological transitions [5], [6]. Deep learning approaches, including convolutional neural network and temporal modeling techniques, have demonstrated strong inference capturing capability for complex spatial and temporal dependencies [4], [18].

Crop phenology, reflects growth stages of a crop over a period of time. Phenology classification is again a challenging task due variety of crops and their spectral signature. Whereas Time-series satellite observations extracts the phenological patterns that can effectively differentiate crop types and monitor developmental stages with spectral signatures of a crop[33],[34].

Machine learning models utilizing these phenological features have shown promising results in crop condition assessment and efficient harvest scheduling [2], [10].

Additionally, recent study shows the use of deep learning techniques for identifying harvest-ready crops at fine spatial resolutions, enabling more precise and timely harvesting operations [11], [13].

Although substantial progress has been made, most existing research addresses crop classification along with phenology of a crop. Although recent study with limited focuses on harvest scheduling and its markable performance not yet achieved. Moreover, challenges such as multi-source data integration, temporal inconsistencies, and adaptability across different agro-climatic regions.

To overcome these limitations, the present study proposes a multi-modal framework for crop classification and harvest scheduling that leverages optical and SAR satellite data, phenological indicators derived from time-series analysis using deep learning approach. The objective is to improve phenology classification accuracy, accurately detect crop growth stages, and facilitate optimized harvest scheduling. By integrating these Multi-modal framework into a unified system, this research aims to contribute toward the development of efficient, scalable, smart, sustainable and precision agriculture solutions.

2. Aims of Research

"Towards Real-Time Agricultural Intelligence: Deep Learning-Based Crop Monitoring and Harvest Decision Support Using Remote Sensing"

The aim of this study is to implement multi-modal deep learning models that combine time-series Synthetic Aperture Radar (SAR) and optical satellite observations to classify and identify key crop growth stages and phenological stages by changing behavior of crop. Further crop classification maps used to translate these insights into accurate harvest scheduling support. By utilizing fusion of radar and optical data, the study intends to provide a reliable, timely, and scalable remote sensing–based decision framework for improved agricultural planning and management across varying environmental and cropping conditions with the help of explainable AI (XAI) approach.

3. Objectives of Study:

1. To study and create multi-crop phenology signature dataset.
2. To develop a multi-modal deep learning framework for multi-crop classification using fused Sentinel-1 and Sentinel-2 time-series data.
3. To develop a phenology model for identifying soybean and maize crop growth stages.
4. To build a harvest scheduling model for soybean and maize crop.
5. To evaluate the performance of developed models.

4. Research Background (Literature Review) and Significance of Research:

Research Background and Significance of Research as follows:

4.1 Literature Review

Zhang H. et al. [1] developed a multi-source system for soyabean grain crop classification in China. Study was conducted in northwestern part of Heilongjiang Province, China, in the month of May to October 2019 time series analysis. This study implemented random forest machine learning algorithm for soyabean crop phenology classification by considering features such as sprectral features, phonological features, Indices computation along with ground truth crop samples. whereas result showed multisource data improved accuracy compared to single source optical image specially in soyabean crop flowering stage.

Dorijan Radočaj et al.[2] comes with system to predict yield of maize and soyabean crop by focusing on phonological stages of a crop. Researcher used seven vegetation indices of sentinel-2 dataset alongwith seven phenology metrics for yield potential prediction. Model train on ground truth yield data of 1000 samples whereas random forest demonstrated good accuracy of 91% compared other machine learning algorithm. Rodrigues, D.M. et.al.[3] reviewed papers for tracking grain production from field to post harvest.

Ma X et al. [4] developed a system for identifying typical crops using multi features from SAR, Optical and dual polarimetric SAR instead of single polarization in the month of April 2023 to overcome disadvantage of single source image. Author constructed three feature sets: a PolSAR feature set, an optical feature set, and an integrated optical and PolSAR feature set and Proposed crop identification DeepLabV3+ model for wheat and rapeseed crop for the study area, located in the central part of Anhui Province, China,. Proposed system developed advance convolution modules to extract features and detect behavior of an model. Sugarcane crop, due to its unique phenological characteristics, long growing cycle, and complex canopy structure, current study could not work efficiently with single date image.

Shahab Aldin Shojaeezadeh et al. [5] developed a system for Sentinel-1 and Sentinel-2 with climate data for crop phenology estimation.where climate features improvised the accuracy of model to predict more than 10 phenological stages on more than 8 crops between 2017 and 2021 in German.

Jha S. K. et al. [6] developed the system for rice phenology classification by integrating weather time series data with remote sensing in Australia during consecutive season in year 2022-2025 season. researcher explored six varieties and three sowing methods for the study alongwith a pre-trained transformer model named as Tabular Prior-data Fitted Network (TabPFN), trained on large synthetic datasets. Precision for PI and flowering predictions, with root mean square errors (RMSEs) of 4.9 and 6.5 days achieved using said model.

Senthil, G. A et al. [7] focuses on Generative AI in Agri: Sustainability in Smart Precision Farming Yield Prediction using high technologies like GPS, Artificial Neural Network, Geographic Information System(GIS), and many deep learning based approaches.

Castro Manrique DR et al. [8] implemented Phenological Monitoring of Irrigated Sugarcane Using GEE, in the Brazilian Semi-Arid. Phenology monitor using NDVI time series data over the period of 19 years from 2001–2020 from available databases on various varieties of sugarcane crop. Phenological Monitoring of Time Series data using TIMESAT software used for exact phenology monitoring of sugarcane crop and deciding harvest schedule based on parameters like start of season, date of cultivation, harvesting dates etc..

Guhan, V et al. [9] Explore multi-factor climate stress scenarios other than temperature to assess model robustness under various climate conditions. Remote sensing, machine learning techniques used for dynamic, real-time calibration and validation of crop models.

Chavan, Y.R et al. [10] developed Crop Yield prediction using Deep Reinforcement Learning by referring multi source data. Researcher developed hybrid approach for yield prediction which combines supervised learning along with reinforcement learning to improve yield prediction accuracy. The model evaluated using ML performance measurement parameters. Future work will focus on enhancing model with more data and computational capabilities.

Sidra Muqaddas et al. [11] employed deep learning based model identifying harvest ready sugarcane farms/field among other popular crops using pixel-wise classification in Punjab, Pakistan using Sentinel-2 data. Pixel classified using evaluation of pixel using twelve spectral bands and six indices. Deep learning models like Convnet, VGG16, ResNet-50, Inception v3 and LSTM achieved good accuracy of 90%. Pixel-wise classification helps to predict yield of sugarcane crop.

Senaras C et al. [12] Demonstrated Planet Fusion, daily analysis-ready data obtained by integrating PlanetScope imagery with sensor like Sentinel-2 and Landsat. Limited Exploration of Temporal and Phenological features in given study. Researcher demonstrated Dynamic Time Warping method for maize phenology classification.

Leandro ER et al.[13] author demonstrated laboratory measurement methods for brix and pol values for classification of Sugarcane maturity using high resolution satellite imagery. Methods shows the correlation of various vegetation indices such as Normalized Difference Water Index (NDWI), Green Normalized Difference Vegetation Index (GNDVI) and the green band.

Yeasin, M. et al. [14] implemented Machine Learning Techniques for Phenology Assessment of Sugarcane crop using SAR and optical data. The model includes feature stack of Sentinel-1 backscatters and parameters VV, alpha and anisotropy and, Sentinel-2

indices, normalized difference vegetation index and weighted difference vegetation index together used to predict and Assessment of Sugarcane crop.

Frank Weilandt et al. [15] proposed a deep learning algorithm for the classification of crop types from Sentinel-1 and Sentinel-2 multi-modal time series data which is based on the celebrated transformer architecture. Model is trained with single train model progressive intra-season classification. Multi modal improved classification accuracy and predicted crop types one month early of harvesting dates.

Waghela et al. [16] have used freely available multispectral satellite imagery of Mumbai, India and have implemented supervised machine learning algorithms on raster data to classify land into categories such as vegetation, water bodies, built-up areas etc. The methodology involved preprocessing of satellite images, feature extraction from spectral bands, and training classification models using labeled datasets.

Swetanisha et al. [17] research mainly focused on comparing different supervised machine learning algorithms to find which works best for Land Use and Land Cover (LULC) classification. The study used Landsat images of twin cities of Odisha i.e., Bhubaneswar and Cuttack and classified the land into categories such as water bodies, vegetation, soil, urban areas etc. The overall process included basic image preprocessing to clean and prepare the data, extracting useful features from different spectral bands, training the models using labelled data, and then testing their performance.

Amini, S., et al. [18] used study area of Isfahan capital city of Isfahan province in Iran applied Random Forest (RF) classification to Landsat time-series data for analyzing urban LULC changes. The authors utilized multi-temporal satellite imagery to detect land transformation patterns and urban expansion. The study highlights the importance of time-series analysis in understanding dynamic urban growth. The work relies on optical and Landsat data and does not integrate SAR imagery, which could improve classification in cloudy or complex urban regions.

Svoboda, J., et al.[19] This Case Study of Czechia employed Sentinel-2 imagery and Random Forest classification for mapping LULUCF categories in Czechia. The study

demonstrated that high-resolution Sentinel-2 data combined with RF can effectively classify forest and non-forest categories with accuracy of 89.1%. The methodology included feature extraction from spectral indices and multi-season imagery to enhance classification performance.

Significance of the Study

Agriculture is increasingly challenged by climate variability, resource constraints, and the need for timely decision-making to ensure food security and sustainable crop production. Traditional crop monitoring and yield estimation approaches rely heavily on ground-based observations, which are often labor-intensive, took much time and coverage is limited. In this context, the integration of remote sensing and deep learning multi-modal approach offers a way toward real-time, scalable, and data-driven agricultural intelligence.

This study is significant as it aims to develop an end-to-end deep learning–based decision support framework for crop monitoring, phenological stage identification, harvest scheduling using multi-modal satellite data in different seasons. By creating a multi-crop phenology signature dataset, the research contributes a foundational resource that captures temporal crop growth dynamics, enabling improved understanding and differentiation of crop behavior across growth stages.

5. National Status

In India, Remote Sensing has been used by researchers for agricultural monitoring along with artificial Intelligence (deep learning and machine learning) vast spatial extent, diversity of cropping systems. In India National agencies such as ISRO and NRSC have operationally utilized optical satellite data for crop area estimation and yield forecasting; however, optical data availability is severely constrained during the kharif season due to persistent cloud cover, leading to temporal data gaps during critical crop growth stages (Ma X2025; Jha, S.K 2025).

To address this limitation, Indian researchers have increasingly adopted microwave remote sensing Synthetic Aperture Radar (SAR) data, specifically Sentinel-1, which provides all-weather condition data, cloud-independent observations and has proven effective for

monitoring crop growth dynamics under tropical monsoon conditions. Recent studies demonstrate that fusion of microwave and optical time-series significantly improves crop classification and growth characterization in Indian agro-ecosystems; however, most of these efforts remain limited to crop type mapping or descriptive temporal analysis using traditional machine learning approaches (Zhang Het al., 2025).

Although phenology plays a critical role in decision-making processes such as harvest scheduling, national-level research explicitly focusing on deep learning-based phenological stage detection using multi-modal SAR–optical time series remains sparse. Existing operational agricultural monitoring systems in India largely rely on rule-based or index-driven methods. These limitations collectively highlight a significant national research gap and proceeds with the need for developing multi-modal deep learning frameworks that integrate SAR–optical time-series data for robust crop phenology detection and operational harvest scheduling under Indian agro-climatic conditions

6. International Status:

Globally, crop classification and phenology detection using multi-temporal and multi modal satellite data have achieved good results. Studies using Sentinel-1 and Sentinel-2 time series have reported high performance for early-season predictions in Germany (Weilandt et al., 2023). In Pakistan, sugarcane classification using Sentinel-2 multispectral imagery and deep learning achieved 95.3% pixel-wise accuracy (Muqaddas et al., 2024).

Brazilian studies using Google Earth Engine and TIMESAT for sugarcane phenology monitoring report an $R^2 > 0.87$ between NDVI-based phenological stages and ground data (Castro Manrique et al., 2024). However, early-stage phenology classification accuracy typically ranges between 60–75%, especially under climate variability or low vegetation signal (Zhang et al., 2017; Dimov et al., 2022). Although deep learning models like Transformers, CNNs, and LSTMs are being increasingly adopted, challenges are still exist in generalizing model (Waters et al., 2025; Leandro et al., 2024; A.K. et al., 2024)

7. Research Hypotheses:

The following hypotheses have been framed which helps in evaluating outcomes of research rather than relying on assumptions:

Null Hypothesis:

Constructing a multi-season, multi-modal phenology dataset will not improve the model's ability to distinguish between crops. Phenology crop classification may not be helpful to decide correct harvest schedule of crop.

Alternative Hypothesis:

Constructing a multi-season, multi-modal phenology dataset will improve the model's ability to distinguish between crops. Phenology crop classification may not be helpful to decide correct harvest schedule of crop.

8. Research Rationale:

Agricultural monitoring is a main component of food security, economic stability, decision making and sustainable development. With increasing demand for agricultural insights, remote sensing technologies offer scalable, cost-effective, and real-time solutions for crop type classification, phonological stage detection, and harvest scheduling.

However, despite advancements in deep learning and satellite data integration, several critical challenges remain unresolved.

Therefore, this research aims to address gaps by:

a. Building a multi-modal and multi-crop phenology dataset.
b. Designing a multi-modal deep learning framework for crop classification and area estimation.
c. Developing a phenology-aware harvest scheduler.
d. Evaluate performance of developed models and validate the result.

This integrated research contributes to data-driven agriculture decision support, aligning with national missions like Digital India and Precision Farming, and sustainable agriculture.

9. Research Methodology:

Data Acquisition:

Crop Study and Dataset Preparation: Multi-crop phenology-wise vector signature dataset will be created by ground truth data collection and crop labelling using softwares like google earth pro, QGIS etc.

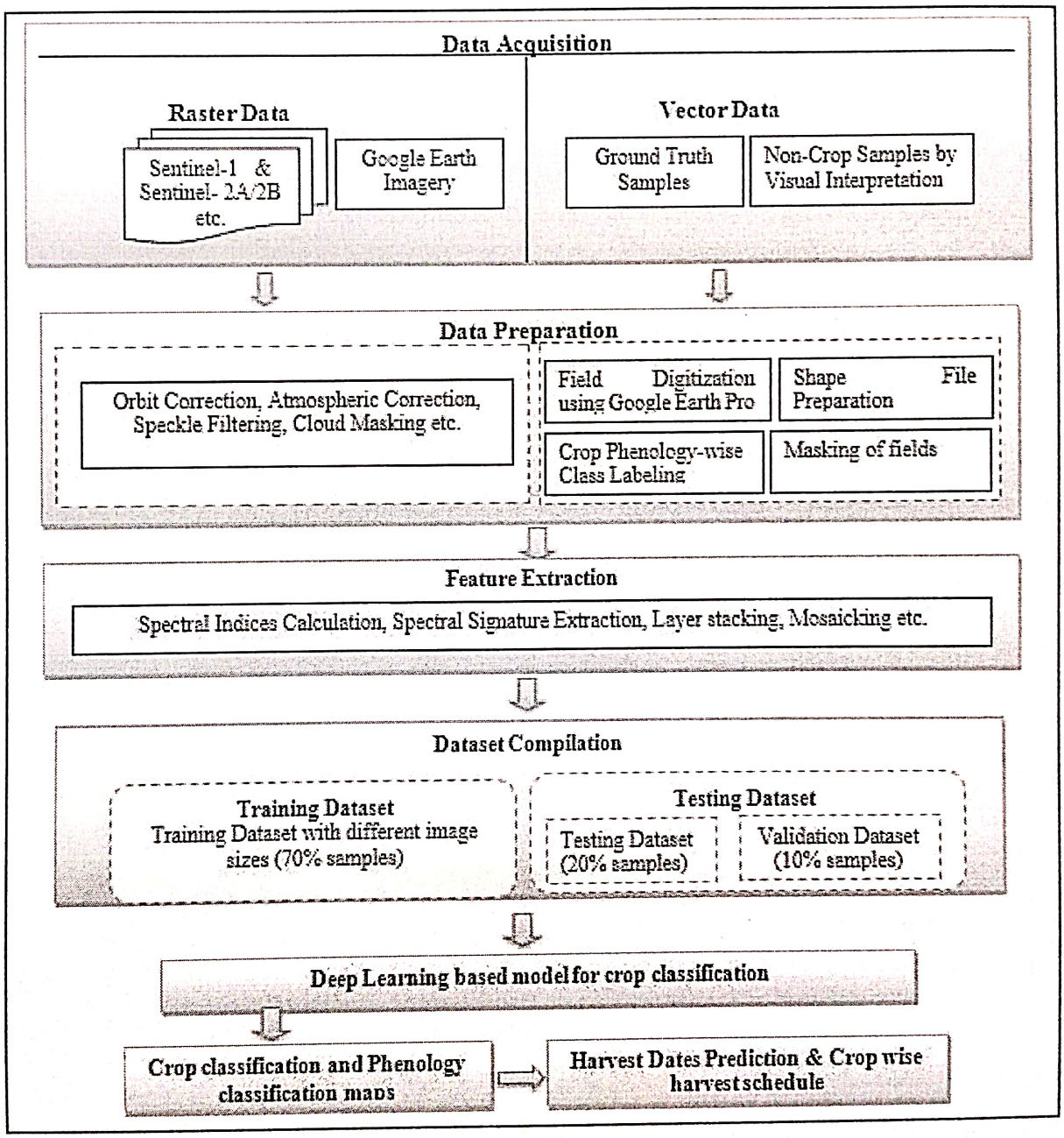

Data Acquisition
Raster Data
Sentinel-1 & Sentinel- 2A/2B etc.
Google Earth Imagery
Vector Data
Ground Truth Samples
Non-Crop Samples by Visual Interpretation
Data Preparation
Orbit Correction, Atmospheric Correction, Speckle Filtering, Cloud Masking etc.
Field Digitization using Google Earth Pro
Shape File Preparation
Crop Phenology-wise Class Labeling
Masking of fields
Feature Extraction
Spectral Indices Calculation, Spectral Signature Extraction, Layer stacking, Mosaicking etc.
Dataset Compilation
Training Dataset
Training Dataset with different image sizes (70% samples)
Testing Dataset
Testing Dataset (20% samples)
Validation Dataset (10% samples)
Deep Learning based model for crop classification
Crop classification and Phenology classification maps
Harvest Dates Prediction & Crop wise harvest schedule

Fig 1. Proposed System crop phenology classification and harvest scheduling

This dataset will have vector data of agriculture and horticulture growing farms. The database includes, the name of farmer, village name, area(in acre/ha'), GPS coordinates, soil type, crop type, variety, inter-cropping info, irrigation type, plantation type, plantation

date, harvesting date, yield etc. along with growing stages of crops i.e. Germination(early), Tillering(Growing), Grand growth(Grown with flowers) , Maturation will be considered. Agriculture crops ground truth data is a geographical information system (GIS) shape files (.kml format) will be collected through fields' survey. Ground Control points will be recorded by the global positioning system (Android Application) device for agriculture crops in study area of nashik district like Soyabean, Tur (Red gram),Sugarcane, Maize, Onion, Wheat, Tomato crop and horticulture crops include Grapes, Pomegranate, Chikoo.

Non Vegetation classes will include other land covers existing in the study area. It includes storages, built-up, residential, industrial building, water body, pastures, rocks and fallow land. Remaining GT point of other objects in the non-agriculture class will be generated through Experts knowledge by visual interpretation using Google Earth Pro platform/

All satellite images of Sentinel-1 & Sentinel-2A/2B utilize in this study will be downloaded from ESA's Copernicus program website (freely available from Copernicus open access hub).Sentinel-2A/2B cloud free images will be downloaded from the website. and for rainy season or cloudy season Microwave RS used.

Data Preparation: In the RS raster images preprocessing done to remove atmospheric effect, radiometric noise correction and geometric errors. This preprocessing normalizes the data. Sentinel-2 series provides multispectral imagery at high spatial resolution from 10 to 60 m. with a 7-day revisit near mid-latitude. In this study satellite bands along with vegetation indices will be used for the multi crop classification along with its phenology, Sentinel-2 spectral bands and vegetation indices such as NDVI, EVI, NDRE, and NDWI will represent crop biochemical and physiological conditions. Temporal metrics including growth rate, peak timing, cumulative vegetation indices, and season length will be extracted to characterize phenological transitions and yield formation.

Feature Extraction: In this study, multi-modal features derived from Sentinel-1 SAR and Sentinel-2 optical time-series data will be used for crop phenology classification and yield estimation. Sentinel-1 features including VV, VH backscatter, VH/VV ratio, temporal backscatter etc. variations will capture crop structural and moisture dynamics, particularly during cloud-affected periods. The fused multi-modal feature set will be integrated into deep learning models to enable robust phenology detection and accurate yield prediction.

Crop & Phenology Classification: Deep learning–based temporal models are employed for crop phenology classification using multi-modal Sentinel-1 SAR and Sentinel-2 optical time-series data. Recurrent architectures such as LSTM and Bi-LSTM will be used to capture sequential crop growth dynamics, while transformer-based models leverage self-attention mechanisms to identify critical phenological transitions across the growing season. Multi-modal fusion is achieved through separate SAR and optical encoders followed by attention-based integration, enabling robust phenology detection under cloud-affected conditions. The proposed framework allows accurate identification of key crop growth stages, supporting downstream applications such as yield estimation and harvest scheduling.

Model Performance Evaluation: The Model evaluated using standard classification metrics, including overall accuracy, precision, recall, and F1-score, computed from the confusion matrix. To address potential class imbalance among phenological stages, macro-averaged and weighted F1-scores will also be reported. Additionally, stage-wise accuracy will be analyzed to evaluate the model's sensitivity to early, peak, and late growth stages. For yield prediction assessment, regression-based metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) will be used to quantify prediction accuracy.

Harvest Dates Prediction: Following phenological stage classification, the predicted temporal progression of crop growth stages will be utilized to estimate crop harvest dates. The harvest date will be determined by identifying the transition to the physiological maturity and senescence stages, as inferred from fused Sentinel-1 SAR and Sentinel-2 optical time-series features. Temporal indicators such as peak vegetation index values, decline in canopy vigor, reduction in SAR backscatter, and duration from sowing to maturity will be integrated within the deep learning framework to estimate harvest timing. For early-season prediction, partial time-series data will be used to forecast the expected harvest date by learning historical growth duration patterns. The performance of harvest date prediction will be evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between predicted and observed harvest dates, expressed in days. This approach enables timely and reliable harvest scheduling support for soybean and maize crops under diverse agro-climatic conditions.

S. No	Crop Name	Crop Duration
1.	**Sugarcane**	~10–18 months (commonly 12 months)
2.	**Maize**	~90–120 days (3–4 months)
3.	**Soyabean**	~90–110 days (3–3.5 months)
4.	**Pigeon Peas (Tur)**	~150–210 days (5–7 months)
5.	**Onion**	~90–150 days (3–5 months depending on season)
6.	**Grapes**	~150–180 days per cycle; perennial vine
7.	**Rice**	~90–150 days (3–5 months depending on variety)
8.	**Wheat**	~120–150 days (4–5 months)
9.	**Tomato**	~90–120 days (3–4 months)
10.	**Cotton**	~150–180 days (5–6 months)
11.	**Bajra (Pearl Millet)**	~75–90 days (2.5–3 months)
12.	**Jowar (Sorghum)**	~100–120 days (3.5–4 months)
13.	**Moong/Urad (Green gram/Black gram)**	~60–90 days (2–3 months)

Table 1: Crop Growth Duration

10. Statistical Plan:

The present study adopts an observational spatio-temporal research design using multi-year time-series remote sensing data to develop a deep learning algorithms for crop classification, phenology detection, yield prediction, and harvest scheduling. Field-level and district-level spatial units will be derived from vector farm boundaries will be used as the primary units of analysis, while temporal observations will be organized at 5–10 day intervals corresponding to Sentinel-1 and Sentinel-2 revisit cycles for Kharif and Rabi seasons. Independent variables will include multi-temporal Sentinel-2 spectral bands, vegetation indices (NDVI, EVI, NDRE, SAVI), phenological metrics (start, peak, and end of season), and Sentinel-1 SAR backscatter features (VV, VH, polarization ratios, texture measures), along with ancillary climatic variables if available. Dependent variables will consist of categorical crop classes, ordinal phenological stages, continuous yield values (kg/ha), and predicted harvest dates.

Data preprocessing will involve noise reduction, outlier detection using inter quartile range and Z-score methods, gap filling through temporal interpolation, and smoothing of time-series profiles.

Model performance will be statistically evaluated using overall accuracy, precision, recall, F1-score, for crop classification; mean absolute error and stage-wise accuracy for phenology detection; and RMSE, MAE, R^2, and Nash–Sutcliffe efficiency for yield prediction.

11. Limitations of the Research:

1. Model development depends on region specific ground survey, still generalize model not yet developed.
2. Sentinel-1 and Sentinel-2A/2B data fusion is an essential and crucial which is hectic and time consuming. Data Preparation and Pre-processing is time consuming process.
3. Sentinel-1 and Sentinel-2A/2B data availability with 7days revisit cycle. So daily real time monitoring not possible with sentinel datasets.
4. Predict harvesting dates depends on many environmental parameters eg. Max temperature, Min Temperature, Base Temperature etc. getting good accuracy for Predicting exact harvesting dates is complex task.

12. Expected Outcomes of Research:

1. Multi-crop phenology dataset for Nashik district.
2. Multi-modal deep learning framework for multi-crop classification.
3. Development of a crop phenology classification module to determine the maturity of crop.
4. Development of harvest scheduling model for soybean and maize crop.
5. Evaluate the performance of developed algorithm and determining best algorithm for crop phenology classification.

13. Conclusion and Future Work

In this research we aim to use Multi-Modal Deep Learning Framework for Crop Phenology Detection which gives the phenology of crop and Harvest Scheduling Using Time-Series SAR–Optical Remote Sensing. This research aims "Towards Real-Time Agricultural Intelligence: Deep Learning-Based Crop Monitoring and Harvest Decision Support Using Remote Sensing". Deep learning models such as CNN, LSTM, RNN will improve accuracy and improves harvest schedule accuracy. Accurate and ground truth phenology data will be collected to train deep learning model. Further crop classification maps used to translate these insights into accurate harvest scheduling support. By utilizing fusion of radar and optical data, the study intends to provide a reliable, timely, and scalable remote sensing–based decision framework for improved agricultural planning and management across varying environmental and cropping conditions.

As future work will focus to develop explainable AI (XAI) approach to create trust on model alongwith extend research to generalize model for other districts and state of India.

14. Bibliography

1. Zhang H, Peng D, Dou C, Lou Z, Zhang X, Yu L, Song K, Zhang Y, Hu J, Zheng S, Lv Y, Liu S, Zhang Y, Peng H. Enhancing early-season soybean identification through optical and SAR time-series integration. *Frontiers in Plant Science*. **2025**; **16**:1656628. https://doi.org/10.3389/fpls.2025.1656628

2. Radočaj, D.; Plaščak, I.; Jurišić, M. Phenology-Based Maize and Soybean Yield Potential Prediction Using Machine Learning and Sentinel-2 Imagery Time-Series. *Appl. Sci.* **2025**, *15*, 7216. https://doi.org/10.3390/app15137216

3. Rodrigues, D.M.; Coradi, P.C.; Timm, N.d.S.; Fornari, M.; Grellmann, P.; Amado, T.J.C.; Teodoro, P.E.; Teodoro, L.P.R.; Baio, F.H.R.; Chiomento, J.L.T. Applying Remote Sensing, Sensors, and Computational Techniques to Sustainable Agriculture: From Grain Production to Post-Harvest. *Agriculture* **2024**, *14*, 161. https://doi.org/10.3390/agriculture14010161

4. Ma X, Li L, Wu Y. Deep-Learning-Based Method for the Identification of Typical Crops Using Dual-Polarimetric Synthetic Aperture Radar and High-Resolution Optical Images. Remote Sensing. 2025; 17(1):148. https://doi.org/10.3390/rs17010148

5. Shojaeezadeh SA, Elnashar A, Weber TKD. A novel fusion of Sentinel-1 and Sentinel-2 with climate data for crop phenology estimation using machine learning. *Science of Remote Sensing*. **2025**; **11**:100227. https://doi.org/10.1016/j.srs.2025.100227

6. Jha, S.K.; Brinkhoff, J.; Robson, A.J.; Dunn, B.W. Integrating Remote Sensing and Weather Time Series for Australian Irrigated Rice Phenology Prediction. *Remote Sens.* **2025**, *17*, 3050.

7. Senthil, G. A., et al. "Generative AI in Agri: Sustainability in Smart Precision Farming Yield Prediction Mapping System Based on GIS Using Deep Learning and GPS."Procedia Computer Science, vol. 252, 2025, pp. 365–380. Elsevier, https://doi.org/10.1016/j.procs.2024.12.038

8. Castro Manrique DR, Lopes PMO, Nascimento CR, Ribeiro EP, Silva ASd. Phenological Monitoring of Irrigated Sugarcane Using Google Earth Engine, Time Series, and TIMESAT in the Brazilian Semi-Arid. AgriEngineering. 2024; 6(4):3799-3822. https://doi.org/10.3390/agriengineering6040217

9. Guhan, V., Annadurai, K., Easwaran, S. et al. Assessing the impact of climate change on water requirement and yield of sugarcane over different agro-climatic zones of Tamil Nadu. Sci Rep 14, 8239 (2024). https://doi.org/10.1038/s41598-024-58771-8

10. Chavan, Y.R., Swamikan, B., Gupta, M.V. et al. Enhanced Crop Yield Forecasting Using Deep Reinforcement Learning and Multi-source Remote Sensing Data. Remote Sens Earth Syst Sci 7, 426–442 (2024). https://doi.org/10.1007/s41976-024-00135-x

11. Sidra Muqaddas, Waqar S. Qureshi, Hamid Jabbar, Arslan Munir, Azeem Haider,A comprehensive deep learning approach for harvest ready sugarcane pixel classification in Punjab, Pakistan using Sentinel-2 multispectral imagery, Remote Sensing Applications: Society and Environment, Volume 35, 2024, 101225, ISSN 2352-9385, https://doi.org/10.1016/j.rsase.2024.101225

12. Senaras C, Grady M, Rana AS, Nieto L, Ciampitti I, Holden P, Davis T, Wania A. Detection of Maize Crop Phenology Using Planet Fusion. Remote Sensing. 2024; 16(15):2730. https://doi.org/10.3390/rs16152730

13. Leandro ER, Heenkenda MK, Romero KF. Estimating Sugarcane Maturity Using High Spatial Resolution Remote Sensing Images. *Crops*. 2024; 4(3):333-347. https://doi.org/10.3390/crops4030024

14. Yeasin, M., Haldar, D., Kumar, S., Paul, R. K., & Ghosh, S. (2022). Machine Learning Techniques for Phenology Assessment of Sugarcane Using Conjunctive SAR and Optical Data. *Remote Sensing*, *14*(14), 3249. https://doi.org/10.3390/rs14143249

15. Weilandt F, Behling R, Goncalves R, Madadi A, Richter L, Sanona T, Spengler D, Welsch J. Early Crop Classification via Multi-Modal Satellite Data Fusion and Temporal Attention. Remote Sensing. 2023; 15(3):799. https://doi.org/10.3390/rs15030799

16. H. Waghela, S. Patel, P. Sudesan, S. Raorane and R. Borgalli, "Land Use Land Cover Classification using Machine Learning," 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 2022, pp. 708-711, doi: 10.1109/ICACRS55517.2022.10029176.

17. Swetanisha, S., Panda, A. R., &Behera, D. K. (2022). Land use/land cover classification using machine learning models. International Journal of Electrical & Computer Engineering (2088-8708), 12(2).

18. Amini, S., Saber, M., Rabiei-Dastjerdi, H., &Homayouni, S. (2022). Urban Land Use and Land Cover Change Analysis Using Random Forest Classification of Landsat Time Series. Remote Sensing, 14(11), 2654. https://doi.org/10.3390/rs14112654

19. Svoboda, J., Štych, P., Laštovička, J., Paluba, D., &Kobliuk, N. (2022). Random Forest Classification of Land Use, Land-Use Change and Forestry (LULUCF) Using Sentinel-2 Data—A Case Study of Czechia. Remote Sensing, 14(5), 1189. https://doi.org/10.3390/rs14051189

20. Jozdani, S. E., Johnson, B. A., & Chen, D. (2019). Comparing Deep Neural Networks, Ensemble Classifiers, and Support Vector Machine Algorithms for Object-Based Urban Land Use/Land Cover Classification. Remote Sensing, 11(14), 1713. https://doi.org/10.3390/rs11141713

21. Ren, S.J.; Guo, H.; Wu, X.; Zhang, L.G.; Ji, M.; Wang, J.; Chen, J. Winter wheat planted area monitoring and yield modeling using MODIS data in the Huang-Huai-Hai Plain, China. Comput. Electron. Agric. 2023, 182, 106049.

22. Kai, P. M., de Oliveira, B. M., & da Costa, R. M. (2022). Deep Learning-Based Method for Classification of Sugarcane Varieties. Agronomy, 12(11), 2722. https://doi.org/10.3390/agronomy12112722

23. Guo, X., Yin, J., & Yang, J. (2024). Fine classification of crops based on an inductive transfer learning method with compact polarimetric SAR images. GIScience & Remote Sensing, 61(1). https://doi.org/10.1080/15481603.2024.2319939

24. Singh, R., Patel, N.R. & Danodia, A. Deriving Phenological Metrics from Landsat-OLI for Sugarcane Crop Type Mapping: A Case Study in North India. J Indian Soc Remote Sens 50, 1021–1030 (2022). https://doi.org/10.1007/s12524-022-01515-w

25. Taylor SD, Browning DM. Classification of Daily Crop Phenology in PhenoCams Using Deep Learning and Hidden Markov Models. Remote Sensing. 2022; 14(2):286. https://doi.org/10.3390/rs14020286

26. Dimo Dimov, Johannes H. Uhl, Fabian Löw, Gezahagn Negash Seboka, Sugarcane yield estimation through remote sensing time series and phenology metrics, Smart Agricultural Technology, Volume 2, 2022, 100046, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2022.100046.

27. Sreedhar, R., Varshney, A., & Dhanya, M. (2022). Sugarcane crop classification using time series analysis of optical and SAR sentinel images: a deep learning approach. Remote Sensing Letters, 13(8), 812–821. https://doi.org/10.1080/2150704X.2022.2088254

28. Zheng Y, Li Z, Pan B, Lin S, Dong J, Li X, Yuan W. Development of a Phenology-Based Method for Identifying Sugarcane Plantation Areas in China Using High-Resolution Satellite Datasets. Remote Sensing. 2022; 14(5):1274. https://doi.org/10.3390/rs14051274

29. Yahui Guo, Yi Xiao, MingWei Li, Fanghua Hao, Xuan Zhang, Hongyong Sun, Kirsten de Beurs, Yongshuo H. Fu, Yuhong He, Identifying crop phenology using maize height constructed from multi-sources images, International Journal of Applied Earth Observation and Geoinformation, Volume 115, 2022, 103121, ISSN 1569-8432, https://doi.org/10.1016/j.jag.2022.103121.

30. Tian, H.F.; Qin, Y.C.; Niu, Z.; Wang, L.; Ge, S.S. Summer Maize Mapping by Compositing Time Series Sentinel-1A Imagery Based on Crop Growth Cycles. J. Indian Soc. Remote Sens. 2021, 49, 2863–2874.

31. Xiao-Peng Song, Wenli Huang, Matthew C. Hansen, Peter Potapov, An evaluation of Landsat, Sentinel-2, Sentinel-1 and MODIS data for crop type mapping, Science of Remote Sensing, Volume 3, 2021, 100018, ISSN 2666-0172, https://doi.org/10.1016/j.srs.2021.100018.

32. Shendryk, Y., Davy, R., & Thorburn, P. (2021). Integrating satellite imagery and environmental data to predict field-level cane and sugar yields in Australia using machine learning. Field Crops Research, 260, 107984. https://doi.org/10.1016/j.fcr.2020.107984

33. Li, X., Du, Z., Huang, Y., & Tan, Z. (2021). A deep translation (GAN) based change detection network for optical and SAR remote sensing images. ISPRS Journal of Photogrammetry and Remote Sensing, 179, 14–34. https://doi.org/10.1016/j.isprsjprs.2021.07.007

34. Isha Ahlawat et. Al Analysis of sentinel-1 data for regional crop classification: a multi-data approach for rabi crops of district Hisar (Haryana). (2020). Journal of Applied and Natural Science, 12(2), 165-170. https://doi.org/10.31018/jans.vi.2263

35. Mandal, D., Kumar, V., Ratha, D., Dey, S., Bhattacharya, A., Lopez-Sanchez, J. M., McNairn, H., & Rao, Y. S. (2020). Dual polarimetric radar vegetation index for crop growth monitoring using Sentinel-1 SAR data. Remote Sensing of Environment, 247, 111954. https://doi.org/10.1016/j.rse.2020.111954

36. Chakhar A, Ortega-Terol D, Hernández-López D, Ballesteros R, Ortega JF, Moreno MA. Assessing the Accuracy of Multiple Classification Algorithms for Crop Classification Using Landsat-8 and Sentinel-2 Data. Remote Sensing. 2020; 12(11):1735. https://doi.org/10.3390/rs12111735

37. Li, S.P.; Gong, Q.X.; Yang, S.L. A Sustainable, Regional Agricultural Development Measurement System Based on Dissipative Structure Theory and the Entropy Weight Method: A Case Study in Chengdu, China. Sustainability 2019, 11, 5313.

38. Heupel, K., Spengler, D. & Itzerott, S. A Progressive Crop-Type Classification Using Multitemporal Remote Sensing Data and Phenological Information. PFG 86, 53–69 (2018). https://doi.org/10.1007/s41064-018-0050-7

39. Zhang, X., Xiong, Q., Di, L., Tang, J., Yang, J., Wu, H., Zhou, W. (2017). Phenological metrics-based crop classification using HJ-1 CCD images and Landsat 8 imagery. International Journal of Digital Earth, 11(12), 1219–1240. https://doi.org/10.1080/17538947.2017.1387296

40. Luna I, Lobo A. Mapping Crop Planting Quality in Sugarcane from UAV Imagery: A Pilot Study in Nicaragua. Remote Sensing. 2016; 8(6):500. https://doi.org/10.3390/rs8060500

41. https://www.nextias.com/blog/agriculture-in-india/

42. Yeasin M, Haldar D, Kumar S, Paul RK, Ghosh S. Machine Learning Techniques for Phenology Assessment of Sugarcane Using Conjunctive SAR and Optical Data. *Remote Sensing*. 2022; 14(14):3249. https://doi.org/10.3390/rs14143249

43. A. K, S. C. S and P. K. H, "Maturity Detection of Sugarcane Using Deep Learning," *2024 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)*, Chennai, India, 2024, pp. 1-6, doi: 10.1109/RAEEUCCI61380.2024.10547906.Chea, Chanreaksa, et al. *"Optimal Models under Multiple Resource Types for Brix Content Prediction in Sugarcane Fields Using Machine Learning."Remote Sensing Applications: Society and Environment*, vol. 26, 2022, article no. 100718, https://doi.org/10.1016/j.rsase.2022.100718.

44. Sreedhar, R., Varshney, A., & Dhanya, M. (2022). Sugarcane crop classification using time series analysis of optical and SAR sentinel images: a deep learning approach. *Remote Sensing Letters*, *13*(8), 812–821. https://doi.org/10.1080/2150704X.2022.2088254

45. Muqaddas, S., Qureshi, W. S., Jabbar, H., Munir, A., & Haider, A. (2024). A comprehensive deep learning approach for harvest ready sugarcane pixel classification in Punjab, Pakistan using Sentinel-2 multispectral imagery. *Remote Sensing Applications: Society and Environment, 35*, 101225. https://doi.org/10.1016/j.rsase.2024.101225

46. Kavats O, Khramov D, Sergieieva K, Vasyliev V. Monitoring of Sugarcane Harvest in Brazil Based on Optical and SAR Data. *Remote Sensing*. 2020; 12(24):4080. https://doi.org/10.3390/rs12244080

Y A

R

Quick Submit

Quick Submit

KJSIEIT

Document Details

Submission ID
trn:oid:::1:3526812520

Submission Date
Apr 4, 2026, 9:59 AM GMT+5:30

Download Date
Apr 4, 2026, 10:01 AM GMT+5:30

File Name
Topic_Approval_Yogita_Algat__04_04_26priny_copy_ver5.pdf

File Size
376.2 KB

23 Pages

6,027 Words

36,525 Characters

*% detected as AI

AI detection includes the possibility of false positives. Although some text in this submission is likely AI generated, scores below the 20% threshold are not surfaced because they have a higher likelihood of false positives.

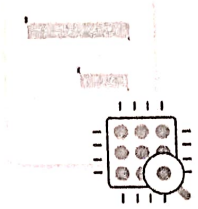
Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Disclaimer
Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.



False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

University of Mumbai

Mahatma Jotirao Phule Bhavan, Vidyanagari, Santacruz (E), Mumbai - 400 098.

RECEIPT NO.: 120 DATE : 04/04/2026

GENERAL FUND - I

Received from ALGAT YOGITA S. the sum of Rupees

Two Hundred Only

by cash being the amount of

PH.D TOPIC APPROVAL FORM FEE

TOPIC APPROVAL FEES Rs. **********200.00

Total: Rs. **********200.00

UNIVERSITY OF MUMBAI Finance & Accounts Cash Unit Vidyanagari Mumbai-400 098.

Cash Receiver's Signature

Finance & Accounts Officer

1. Receipt subject to the realisation of Cheque / Draft etc., it tendered.
2. No. duplicate receipt will be issued.